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A heuristic optimization approach for the scheduling home appliances

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ABSTRACT

In order to develop and execute a demand response (DR) system for a household energy management system, an effective and adaptable energy management architecture is provided in this study. Several issues related to the current home energy management system (HEMS) are among those that do not give their consumers a choice to assure user comfort (UC) or a long-term answer to lowered carbon emissions. Our research suggests a programmable heuristic-based energy management controller (HPEMC) to manage a residential building in order to minimize power costs, reduce carbon emissions, increase UC, and lower the peak-to-average ratio (PAR). In this study, the demand-responsive appliance scheduling problem is solved using an energy management system to reduce the cost and a PAR. Numerous case studies have been used to demonstrate the viability of the suggested method. The simulation results confirmed the effectiveness of the proposed method and that it is capable of running a hybrid microgrid in various modes. The findings indicate that the proposed schedule controller saved 25.98% of energy.

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1. INTRODUCTION

A home energy management system (HEMS), which aids in reducing power usage, particularly during peak load hours, is becoming more significant as a result of concerns about global warming and energy scarcity. HEMS should be considered as a technique to automate power management in a home as well as a way to reduce greenhouse gas emissions. Numerous attempts have been made to develop HEMS systems that combine the control of various home appliances (such as water heaters, air conditioners, refrigerators, electric vehicles, lighting, and others). HEMS can be installed in homes to help with power management by communicating with utilities and home appliances, keeping track of energy use, and receiving information (such tariff pricing) to schedule the operation of home appliances and other equipment to consume less energy. This system can manage distributed energy resources and storage while also optimizing the operating schedules of home appliances [1]–[4].

The desire to create more energy-efficient systems has increased. Motivating customers to consume less energy is the main objective. Advanced technology that involves organizing, observing, and putting into practice the actions and behaviors of electrical utilities is referred to as demand side management (DSM). DSM, a load-side control, becomes crucial in a microgrid. When weak utilities are unable to meet demand due

to a substantial increase in demand, their loads are shrunk. Standard load shedding, however, would be ineffective owing to the emergency, resulting in a loss of supply energy. To save energy, suppliers work to adhere to specific generation schedules. Contrarily, consumers are urged to reduce load usage during peak times or relocate loads to off-peak hours [5].

Storage systems, load curtailment, and DSM are used to address these issues. Load limiting controls the system usage aspect. The most expensive technology in the world is said to be storage systems. However, the application of DSM increases utilisation, heavily regulates loads, and lowers costs. DSM is a reliable tool that satisfies a variety of load shaping objectives. The main responsibility of DSMs is to quantitatively change load utilization by conceptualizing utility or managing load utilisation duties. DSM programs are used to control customers' consumption of energy on both sides. It may keep an eye on the volume of customers and the local generation. Furthermore, without the need for new sources or transmission lines, the available energy resources are expertly controlled through DSM procedures. Peak clipping, direct load control (DLC), load shifting (LS), strategic conservation, strategic load growth, valley filling, and flexible load shape are all examples of "various DSM techniques". By using DLC, a select few of the loads can be remotely terminated at a time of high consumption to prevent system failure. According to the load's dependence on time, LS is mostly used to shift loads from peak to off-peak times. Peak demand is reduced by the peak clipping approach, while off-peak load demand is fulfilled by using the valley filling technique. By combining DSM with different strategies including electricity prices, incentives, and penalties, the amount of electricity consumed could be significantly increased [6].

The two main variations of DSM are incentive- and price-based. Consumers can control their energy intake based on the price of energy in a pricing-centred DSM (dynamic-tariff). Utility cartels have limited controllable loads that are dependent on levels of generation and/or demand in an incentive-centered DSM. DSM encourages consumers to use less energy during peak hours and/or shift energy use to off-peak hours in an effort to level out the power demand curve. To overcome the lack of generation, for example, controllable loads like heating, ventilation, and air conditioning (HVAC) and plug-in electric vehicles (PEV) are judiciously adjusted. The average household load might be significantly increased by such loads, which would further exacerbate the high peak-to-average ratio (PAR) [7]. On sometimes, it is better to follow the generating pattern than to smooth out the curve. It is necessary to control how much energy users use in both scenarios. To engage the various types of loads effectively, a successful DSM method must be developed. Customers might have more freedom if the emissions and operating expenses of the energy sources were reduced. A typical pricing method used to implement numerous demand response programs (DRPs), including LS and DLC, is called time-of-use (ToU). Consumers are urged to manage their electricity use by utilizing ToU tariffs based on advantages from price variations. Consumers can control their electricity costs and pricing for different time periods are known in advance [5], [8]–[11].

2. LITERATURE REVIEW OF THEORETICAL BACKGROUND

Bhamidi and Sivasubramani [12] lay down the foundation for a two-stage optimization model for the optimum planning of smart home renewable energy resources (RERs) and battery integration with the association of prosumer-based energy management. Reference's authors [13]–[15] a case study is used to illustrate the advantages of the proposed intelligent residential energy management system (IREMS) for prosumers of smart residential buildings. Wang *et al.* [16] suggest a ToU price-based demand response (DR) model for the building energy management system (BEMS) that blends building integrated photovoltaic with other generations to maximize the economy and comfort of the occupants through the synergetic dispatch of source-load-storage. By combining machine learning, optimization, and data structure design, Zhang *et al.* [17] developed an interdisciplinary method for developing a DR and HEMS that can satisfy the requirements for practical implementations. Shafie-Khah and Siano [18] proposed a stochastic model of the HEM system by taking into account the unpredictabilities associated with the supply of electric vehicles (EVs) and the production of small-scale renewable energy. As part of a HEMS, Huang *et al.* [19] proposed chance constrained optimization to optimize the operation of appliances in an uncertain environment (HEMS). A novel hierarchical energy management system based on optimization for multi-microgrid was proposed by [20]. To lessen the danger of real-time exposure to energy price and solar power generation uncertainty, [21] suggests a robust-conditional value at risk (CVaR) optimization strategy for day-ahead HEMS. For the purpose of calculating the peak demand in a residential area under four different power demand control scenarios, more realistic and precise analytical models are proposed in [22]. For smart hybrid microgrids, an adaptive energy management system is presented in [23]–[26]. Ahmed *et al.* [27] offer a real-time optimal scheduling controller for HEMS that controls energy consumption using a novel binary backtracking search algorithm (BBSA). Researchers suggested a new on-grid/off-grid energy management system in reference [28], [29] by applying an adaptive neuro-fuzzy inference system.

3. PROPOSED SYSTEM DESCRIPTION

The suggested system's general setup is shown in Figure 1, which consists of a solar system with maximum power point tracking control, an inverter control, a battery, and control. The system includes a battery source as a backup unit for maintaining the microgrid's voltage and frequency as well as for supplying power to important loads during emergency situations. In most cases, the battery is positioned parallel to the photovoltaic system. Batteries either absorb real power or pump it through a converter.

When the battery sends power into a grid or load, the converter runs in boost mode; when the battery takes power from the photovoltaic array, it runs in buck mode. Through a converter, the battery either supplies or consumes real power. The photovoltaic system is typically parallel to the batteries. When the batteries send electricity to a load or the grid, the converter is in boost mode; when they take power from the photovoltaic array, it is in buck mode. Photovoltaic applications frequently choose lead-acid batteries.

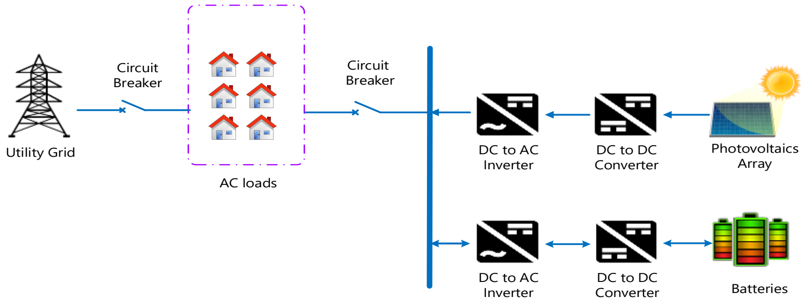

Figure 1. The proposed system structure

3.1. Distributed hybrid energy generation system

The distributed generation systems-based system-level hybrid microgrid model was created, simulated, and tested using Simulink SimPowerSystems. The wind turbine system, solar system, and battery storage system are the hybrid microgrid's three main components. Due to the network complexity, SimPowerSystem phasor mode is used to simulate the hybrid microgrid model in order to run the scenarios more quickly.

3.1.1. Modelling of photovoltaic cell

The equivalent circumference of the solar cell, which can be described as a diode, current source, parallel resistance, and series resistance, is shown in Figure 2. The standard mathematical below defines the photovoltaic cell's current and voltage characteristics (1) [30]–[35]:

$$I = I_{ph,cell} - \underbrace{I_{o,cell}[exp\;((q(V + IR\_(s,cell))/akT) - 1]}_{I_{d,cell}} - \frac{V+IR_{s,cell}}{R_{p,cell}} \quad (1)$$

where, $I_{ph,cell}$ is the photocurrent (A) of the photovoltaic, $I_{o,cell}$ is the saturation current or reversed leakage of the photovoltaic, k is constant of Boltzmann's 1.38×10^{-23} J/K q is electron charge (1.602×10^{-19}C), $R_{p,cell}$ is parallel resistance of photovoltaic, $R_{s,cell}$, is series resistance of photovoltaic. If the parallel and series resistances of the solar cells are not taken into account, a photovoltaic cell model is said to be perfect.

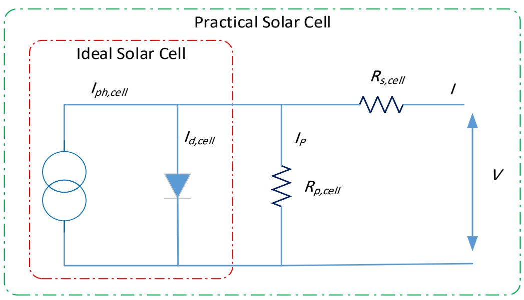

Figure 2. The photovoltaic cell equivalent circuit

3.2. Battery storage system

Batteries are used to store extra energy generated by renewable energy sources. The battery will be discharged to satisfy the load requirement, nevertheless, if the renewable energy producing system is insufficient. A 4,800 (Ah) lithium-ion (Li-Ion) battery unit with a rated voltage of 96 VDC makes up the device. The battery charge/discharge process is governed by (2) and (3) see [36], [37].

$$E_{disch}^{\mathrm{Ni-MH}} = Eo - k\frac{Q}{Q-it}i^* - k\frac{Q}{Q-it}it + e^t \quad (2)$$

$$E_{ch}^{\mathrm{Ni-MH}} = Eo - k\frac{Q}{|it|-0.1Q}i^* - k\frac{Q}{Q-it}it + e^t \quad (3)$$

Li-Ion battery discharge is governed by the following (4) and (5):

$$E_{disch}^{\mathrm{Li-Ion}} = Eo - k\frac{Q}{Q-it}i^* - k\frac{Q}{Q-it}it + Ae^{-Bit} \quad (4)$$

$$E_{ch}^{\mathrm{Li-Ion}} = Eo - k\frac{Q}{|it|-0.1Q}i^* - k\frac{Q}{Q-it}it + Ae^{-Bit} \quad (5)$$

The conditions for discharge and recharge are the same as for nickel-metal hydride (Ni-MH) batteries. The variables and parameters in the aforementioned are:
- K is the polarization constant (Ah^{-1});
- E_o is the voltage of battery;
- Q is maximum battery capacity, in Ah;
- i^* is the filtered low-frequency current dynamics, in A;

3.3. Classification of smart appliances

There are two important types of appliances: the shiftable equipment is managed by EMS over time ($\mathcal{T} = 24$). Suppose a set of manageable devices is represented as $\mathcal{D}_{m,n}$ and $d_m = 1, \dots, \mathcal{D}_{m,n}$ for $n \in \mathcal{N}$ for every customer (6) [38]:

$$\mathcal{L}_{m,n} = \sum_{d_m \in \mathcal{D}_m} \mathcal{L}_{\mathcal{D}_{m,n}} \quad (6)$$

where $\mathcal{L}_{m,n}$ is appliances load and $\mathcal{D}_{m,n}$ is appliances set. Nonshiftable devices cannot be shifted to hours of off-peak for minimize cost, i.e., the consumption of power profiles of devices such as the refrigerator, light, and TV. A nonshiftable device of the costumer $n \in N$ is identified (7) as:

$$\mathcal{L}_{nm,n} = \sum_{d_{nm} \in \mathcal{D}_{nm}} \mathcal{L}_{\mathcal{D}_{nm,n}} \quad (7)$$

Community electricity is produced from renewable electricity sources (RES) in the form of community microgrids. The goal of the optimization model is to plan limited energy resource for appliances according to their needs for periods and electricity costs. Electrical applances work under the electricity tariff 24 h ahead of time of use. Where, $\mathcal{L}^{n,t}$ is a total consumption of power profile of customers $n \in \mathcal{N}$ in $t \in \mathcal{T}$ slot time (8) and (9).

$$\mathcal{L}_d^n = \mathcal{L}_{m,n} + \mathcal{L}_{nm,n} \quad (8)$$

$$\mathcal{L}_d^{n,t} = \sum_{t=1}^{\mathcal{T}} \mathcal{L}_d^{n,t} \quad (9)$$

where, $\boldsymbol{\mathcal{L}_{\mathcal{T}}}$ is a total power of all customers (10).

$$\mathcal{L}_{\mathcal{T}} = \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \mathcal{L}_d^{n,t} \qquad \forall t \in \mathcal{T} \quad (10)$$

Each consumer has a separate power consumption schedule that decreases bills and demand peak in a different time frame every day. The PAR ratio is calculated by the combined power profiles (11)-(13) [39].

$$\mathcal{L}_{peak} = max\mathcal{L}_{\mathcal{T}} \quad (11)$$

$$\mathcal{L}_{avg} = \frac{1}{\mathcal{T}} \sum_{n=1}^{\mathcal{N}} \sum_{t=1}^{\mathcal{T}} \mathcal{L}^{n,t} \qquad \forall\, t \in \mathcal{T} \quad (12)$$

$$PAR = \frac{\mathcal{L}_{peak}}{\mathcal{L}_{avg}} \tag{13}$$

3.3. Problem formulation

To minimize the objective function of cost of devices in individual and community consumer (14):

$$\begin{aligned} min\mathfrak{P}_n = \sum_{n\in\mathcal{N}}\sum_{t\in\mathcal{T}}\sum_{q\in\mathcal{Q}}\sum_{d\in\mathcal{D}}(\alpha_{q,d}^{n,t} \times \mathcal{L}_{q,d}^{n,t} \times \mathfrak{P}_{\mathcal{E}}^{n,t} - \beta_r^{n,t} \times \mathfrak{S}_r^{n,t} \times \mathfrak{P}_r^{n,t} \\ + \gamma_{\mathfrak{P}}^{n,t} \times \mathfrak{L}_{\mathfrak{L}}^{n,t} \times \mathfrak{P}_{\mathfrak{P}}^{n,t}) \end{aligned} \tag{14}$$

where, $\gamma_{\mathfrak{P}}^{n,t}$ is the decision flexible, $\mathcal{N}$ is the total amount of users, $\mathcal{T}$ is the time, $\mathcal{Q}$ is the type of load, $\mathcal{D}$ is the total number of devices, $\alpha_{q,d}^{n,t}$ is the decision variable for the appliances, $\mathfrak{P}_{\mathcal{E}}^{n,t}$ is the electricity, $\mathfrak{S}_r^{n,t}$ is the decision variable for energy, and $\mathfrak{L}_{\mathfrak{L}}^{n,t}$ is the electricity storage at time t, $\mathcal{L}_{q,d}^{n,t}$ is the power profile of the house devices.

3.3.1. Preference of operation period

The binary matrix is used to create a factor that is ready to use. This requires the ready-to-use slot $w_{q,d}^{n,t}$ to run the devices over time. Home users typically use a computer more frequently throughout the day before switching to other devices (15).

$$\mathfrak{P}_1: \alpha_{q,d}^{n,t} = \alpha_{q,d}^{n,t} \times w_{q,d}^{n,t} \tag{15}$$

3.3.2. Variable decision

Constraint $\mathfrak{P}_2$ is the decision variable of the device ON/OFF. Constraints $\mathfrak{P}_3$ is decision variable of user for self generation power. If $\beta_r^{n,t} = 1$, user is a prosumer and $\beta_r^{n,t} = 0$ for user is a consumer. Customers buy electricity from the local power grid or microgrid (16)-(18).

$$\mathfrak{P}_2: \alpha_{q,d}^{n,t} \in \{0,1\} \qquad \forall q, t \in \mathcal{T} \tag{16}$$

$$\mathfrak{P}_3: \beta_r^{n,t} \in \{0,1\} \qquad \forall q, t \in \mathcal{T} \tag{17}$$

$$\mathfrak{P}_4: \gamma_{\mathfrak{P}}^{n,t} \in \{0,1\} \qquad \forall q, t \in \mathcal{T} \tag{18}$$

3.3.3. Devices task

Knowing the lifespan of intelligent devices is essential for the measurement of energy profiles. $t_{q,d}$ is the operation time of d_{th} devices in the T slot time in $\mathfrak{P}_5$. $\alpha_{q,d}^{n,t}$ is the decision variable to turn on/off the device. The constraints $\mathfrak{P}_5$ and $\mathfrak{P}_6$ are constant times to complete a task, and they must be left on at all times $\mathcal{T}$, until it has finished a task. For instance, after a washing machine starts up, it continues to run constantly until the designated end time, $\mathfrak{P}_6$ is formulated. ts is the devices starting time (19) and (20) [40]-[48].

$$\mathfrak{P}_5: \sum_{t=1}^{\mathcal{T}} \alpha_{q,d}^{n,t} = t_{q,d} \qquad \forall q, t \in \mathcal{T} \tag{19}$$

$$\mathfrak{P}_6: \sum_{t=ts}^{ts+t_{q,d}-1} \alpha_{q,d}^{n,t} = t_{q,d} \qquad \forall q, t \in \mathcal{T} \tag{20}$$

3.3.4. Devices priority

The appliance will turn on once another system has finished its service cycle. A dryer won't turn on until the laundry has gone through its whole working cycle. s_i is the collection of these cargoes. The devices from each group are chosen for each time period by the decision variable (21).

$$\mathfrak{P}_7: \sum_{d\in s_i} \alpha_{q,d}^{n,t} = 1 \qquad \forall q, t \in \mathcal{T} \tag{21}$$

3.4. Price

The group micro grid transmits the pricing signal. For our analysis, the community may choose to export and import a certain amount of energy. Electronic grid transactions make use of the dynamic pricing system. Prices cannot be changed after publishing because it is assumed that they are approved. Customers are

free to select the pricing structure. At various periods during the day, the same load will have varying charges. Nighttime grid electricity is continuously scarce and expensive, and vice versa. The cost of energy is influenced by the amount of energy used and the time of day it is used (22) [49]–[55].

$$\mathfrak{P}_{\mathcal{E}}^{n,t} = \begin{Bmatrix} \mathfrak{P}_{r} = 0.3 & if\ r_{sa} = 1 \\ \mathfrak{P}_{\mathcal{b}} = 0.7 & if\ \mathcal{E}_{\mathcal{b}a} = 1 \\ \mathfrak{P}_{g} > \mathfrak{P}_{\mathcal{b}} > \mathfrak{P}_{r} & O.W \end{Bmatrix} \quad (22)$$

where $\mathfrak{P}_{\mathcal{E}}^{n,t}$ is the electricity tariff, $\mathfrak{P}_{r}$ and $\mathfrak{P}_{\mathcal{b}}$ are electricity prices from the community micro grid and $\mathfrak{P}_{g}$ is a utility grid purchase.

4. PROPOSED OPTIMIZATION METHOD

4.1. Genetic algorithm

The genetic algorithm (GA) is an optimization algorithm that draws inspiration from the genetic development of biological things. The length of chromosomes indicates the number of appliances that need to be scheduled, and the genetic chromosomes of GA represent the on/off status of appliances. The population is first created at random, then fitness is assessed using our objective function. The GA's crossover and mutation phases are then used to create a new population after fitness evaluation. At each iteration, crossover and mutation create a new population. In the crossover, new offspring are produced by choosing step two parents. We employ mutation to prevent repetition and produce randomness in the outcomes. A population is created after crossing and mutation, and fitness is assessed. To arrive at the best overall solution, recent results from a fitness examination are contrasted with earlier results [56]–[60].

5. SIMULATIONS RESULTS

Three intelligent homes are envisioned for scheduling, with each home having many devices. For a fair comparison of the electricity bills for the three families, we took into account the identical energy usage for each user. A detailed description of each device is provided in Table 1. The appliances have been divided into three groups: interruptible, scheduled, no-schedulable, and interruptible with no schedule.

Table 1. Microgrid devices characteristics

Type	Daily usage	Power (kW)	Devices
Devices of fixed loads	24	0.25	Refregrator
	5	3	HVAC
	8	0.2	TV
	9	0.25	Lights
	18	0.3	PC
	24	0.1	Cameras
	3	1	Oven
Devices of non shiftable loads	3	1.5	Washing machine
	4	1	Clothes dryer
	2	1	Dishwasher
	2	1.2	Electric frying pot
Devices of shiftable loads	6	1.5	Water heater
	3	1.7	Vacuum cleaner
	4	1	Water pump
	2	3.5	gayser

5.1. Result without corrective method

The simulation is run to confirm the effect of the ToU signal on the user's electricity bill. The cost of energy usage and generation determine how erratic and time-dependent power prices are. The costs of production are, however, confidential in a number of ways. We therefore assume for the analysis that the generation with high ToU rates will rise. The HEMS includes a graphical user interface (GUI) and associated software to make it easier for consumers to monitor their power usage and the overall cost of the microgrid devices; Figure 3 shows the power consumption of all homes without the corrective technique in operation. The suggested HEMSs cost- GUI is depicted in Figure 4 without the corrective approach.

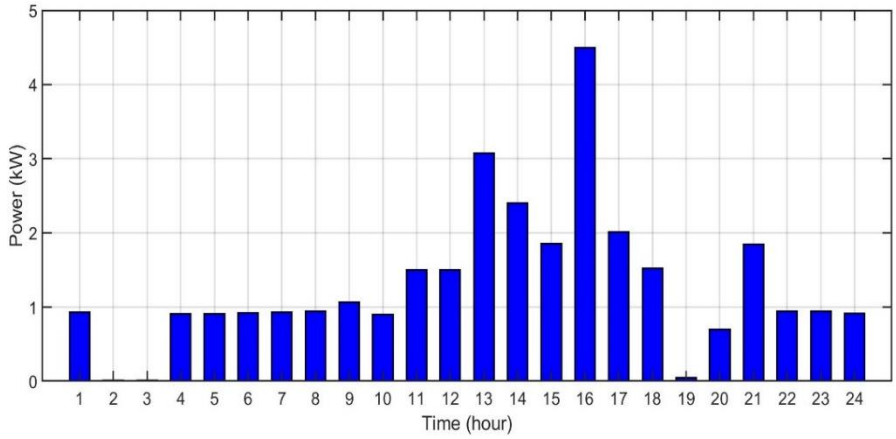

Figure 3. Load profiles power of the suggested home structure without corrective method

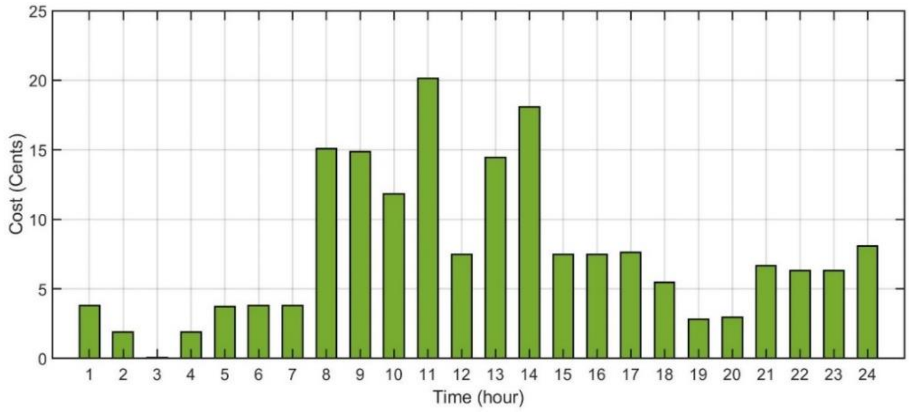

Figure 4. cost of the suggested home structure's load profiles in the absence of a corrective measure

5.2. Result with corrective method

The proposed energy management system then has been incorporated into power system and the resultant system has been simulated to investigated the effect of the proposed management system. Figure 5 illustrates the power GUI of the proposed home management system after implementing the optimization algorithm while Figure 6 shows the cost.

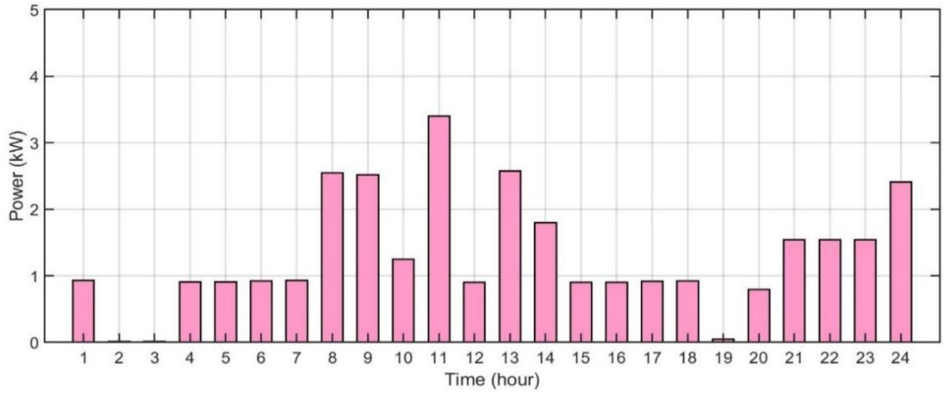

Figure 5. Load profiles power of the proposed system after implementing the GA algorithm

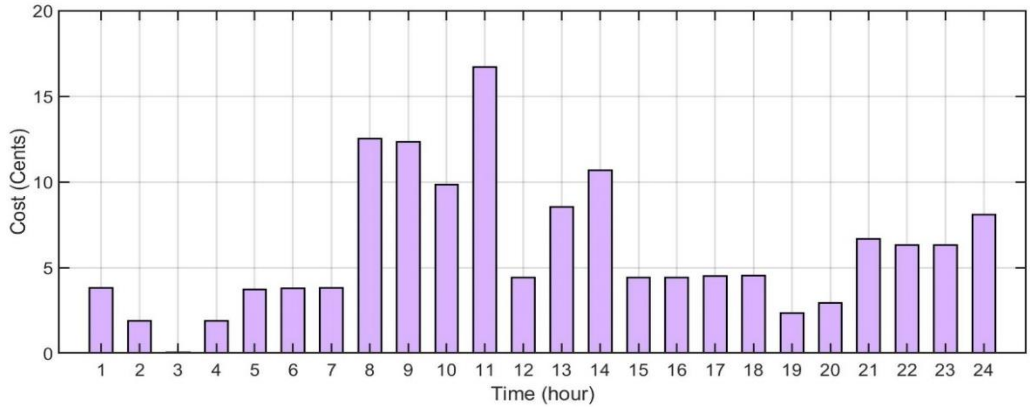

Figure 6. Cost profiles for the suggested system following the use of the GA algorithm

6. CONCLUSION

In order to lower the cost of the residential area's electricity, we suggested an energy management system. The side effects of our effort include decreasing carbon emissions, lowering PAR, and raising user comfort (UC). We gave the idea of a smart house with various smart gadgets some thought. RESs were incorporated into the smart house as well. The energy storage system was also thought to use energy effectively. Furthermore, we used GA methods to resolve the appliance scheduling issue. The suggested algorithm effectively schedules smart appliances, according to simulation findings. Several MATLAB experiments were run to evaluate the effectiveness of the suggested system models presented in this research. By utilizing the GA algorithm, the schedule controller suggested in this research was able to reduce energy consumption for the residence by 25.98%.

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